Paper No. 93-3050

AN ASAE/CSAE MEETING PRESENTATION

NEURAL NETWORK CLASSIFICATION OF UNDAMAGED AND DAMAGED PEANUT KERNELS USING SPECTRAL DATA

by

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Written for presentation at the
1993 International Summer Meeting
sponsored by
THE AMERICAN SOCIETY OF AGRICULTURAL ENGINEERS
THE CANADIAN SOCIETY OF AGRICULTURAL ENGINEERING

Spokane Center
Spokane, Washington
20-23 June 1993

SUMMARY:

In order to improve the accuracy of measuring peanut quality in grade samples, a neural network (NN) was used to classify undamaged and damaged peanut kernels using spectral reflectance data from 400 nm to 700 nm. Results showed kernel classifications were best, network errors minimized, and speed of convergence greatest when the NN was set up with 20 or more hidden nodes, and trained with a learning rate of 0.9, a momentum of 0.45 or less, and using 520,000 or more learning events.

KEYWORDS:

Network, Artificial Intelligence, Peanuts, Grading, Inspection

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INTRODUCTION

Trained inspectors visually inspect approximately 600,000 samples of farmers' stock peanuts (*Arachis hypogaea*, L.) each year for damaged peanut kernels in addition to determining other quality factors. The complete inspection process includes mechanically cleaning, shelling, and sizing a 500 g sample of peanuts in preparation for the visual inspection. During the visual inspection, the inspector examines each peanut greater than 6.35 mm in diameter for discolorations or insect damage, and all peanuts for fungal damage. Freezing temperatures, excessive heat during drying, insect damage, and fungal damage are among the factors that adversely affect peanut quality and typically result in a discoloration on the surface of the peanut kernel. The inspectors receive about two days of training before the beginning of each farmers' stock harvest season and are provided with color charts to aid in the damaged kernel classification. Certain types of damage categories require the kernel be more than 25% discolored before the kernel is considered damaged (USDA, 1991). Certain damage types, such as the presence of *Aspergillus flavus*, or excessive amounts of some damage types, such as freeze damage, can result in a reduction in the load value by about 75% (USDA, 1992). Some damage sources, such as damage due to insects, provide a means for the invasion of *A. flavus* which can produce aflatoxin, a suspected carcinogen. Thus, it is important that damaged kernels be accurately and consistently identified to insure the seller and buyer receive or pay a fair price for the peanuts and to insure that peanuts at risk for containing aflatoxin are accurately identified for subsequent segregation.

Previous research shows the inaccuracies in the present grading system, some of which are due to inspector subjectivity. Dowell (1992a) estimated that inspector subjectivity contributed to about 24% of the total error in grading peanuts. Other research shows there are errors associated with using visual damage assessments to segregate edible from inedible peanuts (Blankenship and Dorner, 1991). Proper segregation is important to prevent mixing aflatoxin suspect peanuts with good peanuts. When aflatoxin suspect peanuts are mixed with good peanuts, subsequent cleanup to reduce aflatoxin to safe levels can cost about 50% of the value of the peanuts and cleanup is becoming increasingly more difficult as consumers demand tolerance levels be reduced. Thus, a means of accurately and consistently identifying damaged kernels in grade samples is needed.

LITERATURE REVIEW

Previous research to remove subjectivity from determining damaged kernels concentrated on gathering spectral and spatial information from the kernels. Dowell (1992b) correctly classified 63% of the damaged and 100% of undamaged kernels using a black and white machine vision system which measured spectral and spatial information. Subsequent tests resulted in correct classification of 79% of damaged and 100% of undamaged kernels using a colorimeter which measured only spectral information. Correct kernel classifications were 93% for damaged and 99% for undamaged when selected wavelengths between 400 and 700 nm from a spectrophotometer were used. However, even one *A. flavus* kernel can contaminate several tons of peanuts and since undamaged kernels account for about 90% of the lot value, the classification of undamaged and damaged kernels needs further improvement. Thus, methods of classifying kernels using the full spectral curve were investigated. The Kolmogorov-Smirnov (KS) statistical test (Steel and Torrie, 1980) can be used to determine if two curves come from the same population and was investigated but resulted in very poor kernel classifications (Dowell, 1992b). The KS test is sensitive to peaks in the spectral curve, but is not sensitive to where the peaks occur. Visual differences between undamaged and damaged spectral curves can be noted, thus it was hypothesized that artificial intelligence techniques, such as neural networks, may aid in kernel classifications.

Neural networks (NN) are artificial intelligence systems developed to simulate some of the organizational principles found in the human brain (Bochereau et al., 1992). NN are particularly effective when the data sets are large, there does not exist expertise in analyzing the data, and the decision required is binary (Dyer, 1989) which is the case with classifying undamaged and damaged peanut kernels. NN consist of processing elements (PE) that can consist of many nodes. Each node can receive many inputs and computes a single output. These processing elements are arranged in layers. Within a PE, each input is multiplied by a corresponding weight. The products are summed and the PE's output is computed from the sum via a transfer function. The output is available as an input to any or all of the PE's in the next layer.

During training, the NN output is compared to a target output and an error calculated. The error is propagated backward from the output PE to the input PE. Weights at each PE are adjusted to minimize the error. The training cycle is repeated until the network error is acceptably low. Back propagation learning is the most common NN type used although it has the drawbacks of being slow, requires much training, may exhibit temporal instability or oscillate, and can become stuck at a local minima (Nelson and Illingworth, 1991).

The variables that affect the error and the training speed of the NN are the number of learning events, the learning rate, momentum, and number of nodes. The number of learning events required to train a NN varies with the problem. Too few learning events results in inadequate learning of the training data while too many learning events results in memorization of the training data and poor performance with new data. The learning rate of the NN determines how much of the error to propagate back into the proceeding nodes and affects the speed of convergence of the network. A lower learning rate may be slow but more accurate, whereas a higher learning rate may not converge. The momentum of a NN determines how much the node weights should be changed in subsequent steps (Nelson and Illingworth, 1991). A mathematically rigorous description of a NN can be found in other publications such as those by Nelson and Illingworth (1991) or Rigney and Kranzler (1989).

No single NN works best for all situations and no rigid guidelines exist for selecting the optimal neural network configuration or parameters. These parameters depend on the application and may be determined and optimized experimentally.

Neural networks are finding commercial application in such areas as canceling noise in telecommunications, mortgage risk evaluation, bomb detection at airports, process control, and component checking (Nelson and Illingworth, 1991; Dyke, 1989). Research is ongoing in the agricultural sector to apply NN to quality evaluation. Thai and Shewfelt (1990) used NN to link human sensory judgments to physical measurements of external color for tomato and peach. Zhuang and Engel (1990) showed NN can replace expert systems in such applications as herbicide selection or selecting grain marketing alternatives. Thai et. al (1991) used NN to estimate green tomato maturity from X-ray computed tomography images. Whittaker et. al (1991) used NN to grade beef, Rigney and Kranzler (1989) used NN to grade pine tree seedlings, and Brons et al (1991) used NN to evaluate potted plant beauty. The success of the above NN applications warrants research into the application of NN to classify undamaged and damaged peanuts using spectral information. Thus, the objective of this research was to investigate the use of NN to utilize all spectral information from 400 to 700 nm to classify damaged and undamaged peanut kernels.

PROCEDURES

Data Collection

Spectral curves were obtained from approximately 600 damaged and 200 undamaged kernels selected from the 1989 and 1990 crop years. Kernels were stored in banks for later reference. Kernel damage was of the following types: black spots, entirely black, brown, insect holes, *A. flavus*, white mold, purple seed coats, yellow discolorations, and freeze damage. Undamaged categories consisted of visibly good redskin and blanched kernels.

The spectral curves were collected using a X-Rite 968 reflectance spectrophotometer which measured kernel spectral reflectance from 400 nm to 700 nm in 10 nm intervals. The spectrophotometer specifications include a 0 degree illumination angle, 45 degree viewing angle, and an 8 mm diameter target window. The damaged areas filled the target window in most cases. Each side of each kernel was hand placed over the target window, thus a total of 1200 spectras from damaged kernels and 400 spectras from undamaged kernels were collected. Each spectra was treated as a separate kernel, thus essentially doubling the amount of kernel information in the data set. If one side of a damaged kernel appeared undamaged, then that spectra was treated as an undamaged kernel spectra. The damaged kernel data was combined into one data set and compared to the combined undamaged redskin and blanched data set. CIE illuminant C was used to calibrate the meter. The data was stored in an ASCII file for subsequent analysis.

Neural Network

A back propagation NN was developed using the NeuralShell software package. Relative reflectance at 10 nm increments was used as input to 31 nodes in the input layer. Training proceeded until manually terminated or until the NN converged to a user-selected error. NeuralShell allows the number of nodes, number of layers, learning rate, learning events, and momentum to be varied. The NN was a fully connected, feed forward, supervised network, and used a sigmoid transfer function. The NN output threshold was set to 0.50 and the learning threshold was set to 0.0001. A kernel was classified as undamaged if the output was greater than 0.50 and damaged otherwise.

Thai and Shewfelt (1990), Rigney and Kranzler (1989), and Bochereau et al. (1992) showed no benefit of using more than one hidden layer. Thus, we used only one hidden layer in this study. Nelson and Illingworth (1991) noted NN parameters such as learning rate, number of nodes in the hidden layer, momentum, and learning events must be determined experimentally, thus a study was designed to examine the effects of these parameters on the accuracy of classifying undamaged and damaged peanut kernels. Table 1 shows the values for each parameter tested. Each NN run was terminated by the user when the number of learning events exceeded the desired number listed in Table 1. The NN program selects one tenth of the total data set for the test data set. This data set was used for all tests. Approximately 1400 spectras were used for training. Forty-four un damaged and 112 damaged kernel spectras were used for testing classification error. The accuracy of the NN when classifying these 156 kernels was compared to the classification accuracy of previous techniques reported by Dowell (1992b) which used magnitudes of and line slopes between three statistically selected wavelengths and colorimeter tristimulus values.

Comparisons between variables were made using SAS (1987) statistical analysis software. The three levels of the four variables resulted in 81 possible combinations. When determining the effects of the three levels of a given variable on the classification accuracy, the results from the other three variables were averaged together resulting in 27 observations for each level of each variable. Likewise, the interaction between two variables was compared by averaging the remaining two variables resulting in 9 observations for each interaction. An interaction of three variables resulted in 3 observations for each comparison.

RESULTS AND DISCUSSION

Table 2 shows the percentage of undamaged and damaged kernels correctly classified, the network error, and the number of learning events at convergence for each level of each variable. The best classifications and smallest network errors occurred on test numbers 68 and 69 when using 40 nodes, a learning rate of 0.6, a momentum of 0.45, and greater than about 500,000 learning events. These combinations resulted in correct classification of 87.82% of all kernels, a network error of 0.036, and converged after 269,000 learning events. Test numbers 41 and 42 had about 86% correct classification. The only difference being that tests 41 and 42 used 20 nodes and had slightly higher network errors.

Table 3 shows the statistical comparison of the levels of each variable. The data shows that the correct classification of undamaged kernels increased and network error decreased as the number of nodes increased to 20 and leveled off thereafter. In addition, more learning events resulted in significantly better (P=0.05) classification of undamaged kernels, significantly better total classification, and resulted in significantly lower network error. Momentums less than 0.9 had significantly lower network errors. Learning rate did not have a significant effect on kernel classification or network error.

Table 4 shows the significance of each variable and of each interaction. The significant effect ($P <= 0.05$) of the number of nodes, learning events and momentum on network errors shown in Table 3 is again shown by the probability values in Table 4. By itself, learning rate had no significant affect on classifications. This observation was also noted by Thai and Shewfelt (1990) who reported no effect of learning rate on neural network performance. Several interactions were significant ($P <= 0.10$) but no clear conclusions could be drawn except for the fact that the interaction of nodes and learning rate was significant for all kernel categories and for network error. All variables contributed to at least one significant interaction when combined with other variables.

Next, linear and quadratic lines were fit to the data to further study the trends in the data. Table 5 shows the coefficients of determination (R^2) for each variable. All R^2 values were less than 0.30. This shows that any one variable accounts for less than 30% of the total variation. The R^2 values improve some with some quadratic analyses, but are all still less than 0.30. The number of nodes received consistent benefit from the quadratic regression applied to the kernel classifications and to the network error. This further supports the means in Table 3 which shows, for undamaged kernels and for network error, that classifications and errors improve as nodes increase to 20, then classifications do not improve further. Thai et al. (1991) also noted that classification accuracy increased as the number of nodes increased to 4, then accuracy decreased. Nelson and Illingworth (1991) also described this quadratic effect of nodes on classifications by noting that too many nodes in the hidden layers make it hard for the network to generalize. Too few nodes leads to an inability to form adequate midway representations and to encode what the network thinks are significant features of the input data. The small improvements in learning events linear and quadratic R^2 values for undamaged and total kernels further support the significant differences and linear trends seen in Table 3. A stepwise linear regression shows that combining all variables improves the R^2 value only to 0.128, 0.029, 0.099 and 0.442 for undamaged kernels, damaged kernels, total kernels, and network error, respectively.

Table 6 shows the effect of the variables on the speed of convergence for the different number of learning events. Convergence occurred when the minimum error was reached for a specific number of learning events. For 26,000 learning events, the speed of convergence increased as nodes increased. For 1,000,000 learning events, speed of convergence increased as momentum and learning rate increased. It should be noted that although convergence was reached when trained with only 26,000 learning events, Table 3 shows significantly less network error and significantly better kernel classifications when trained with 520,000 or more learning events.

A comparison of the results from this NN to previous research where kernels were classified using statistically selected wavelengths and line slopes from data obtained using a spectrophotometer and using L* a* b* color space values from a colorimeter is shown in Table 7. The procedures used to collect this data are reported by Dowell (1992b). The same kernels were used in the three studies so direct comparisons could be made. Table 7 shows the NN classified undamaged, damaged, and total kernels better than the colorimeter method and classified damaged and total kernels better than the 3 wavelength method. The total kernel classifications for the NN were about 5% better than the colorimeter method and about 13% better than the 3 wavelength method. This improvement of NN over statistical techniques is similar to those reported by Bochereau et al. (1992), Whittaker et. al (1991), and Brons et al. (1991).

Future research will focus on separating the undamaged and damaged categories into subgroups including undamaged blanched, undamaged redskins, purple, black, brown, etc. to see which categories can be predicted with the most accuracy.

SUMMARY

Results showed that kernel classifications were best, network errors minimized, and speed of convergence greatest when the NN was set up with 20 or more nodes, used with a momentum of 0.45 or less, trained with 520,000 or more learning events, and when used with a learning rate of 0.9. The learning rate did not affect the NN performance but did affect the speed of convergence. The two most accurate kernel classifications NN settings occurred when the NN parameters were set at 40 nodes, a learning rate of 0.6, a momentum of 0.45, and learning events of 520,000 or 1,000,000. These settings resulted in a minimum network error of 0.036 and 87.82% of all kernels correctly classified. Convergence at this setting occurred at 269,000 learning events. When compared to statistical means of classifying kernels using data from specific wavelengths or data from a colorimeter, the NN correctly classified about 5% and 13% more kernels, respectively, than the two other methods.

ACKNOWLEDGEMENT

The author thanks Harry T. Sheppard for his assistance in running the neural network and analyzing the data.

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Table 1. Neural Network variables used to classify undamaged and damaged peanut kernels.

Number of Hidden Layer Nodes	1	20	40
Learning Rate	0.1	0.6	0.9
Momentum	0	0.45	0.9
Learning Events	~26,000	~520,000	~1,000,000

Table 2. Results from a neural network used to classify undamaged and damaged peanut kernels.

Test Number	Number of Nodes	Learning Rate	Momentum	Learning Events	Undamaged Kernels Correctly Classified %	Damaged Kernels Correctly Classified %	Total Kernels Correctly Classified %	Network Error[1]	Learning Events at Convergence[2]
1	1	0.1	0.00	28650	84	62.26	69.23	0.058656	27250
2	1	0.1	0.00	525600	48	86.79	74.36	0.049652	513800
3	1	0.1	0.00	1000000	54	86.79	76.28	0.048937	988600
4	1	0.1	0.45	25800	36	90.57	73.08	0.062228	4000
5	1	0.1	0.45	520000	42	83.02	69.87	0.060017	422600
6	1	0.1	0.45	1152000	42	83.96	70.51	0.060017	422600
7	1	0.1	0.90	26000	32	98.11	76.92	0.059282	7200
8	1	0.1	0.90	599400	34	96.23	76.28	0.057587	61200
9	1	0.1	0.90	1245200	34	96.23	76.28	0.057587	61200
10	1	0.6	0.00	26000	34	94.34	75.00	0.059335	24200
11	1	0.6	0.00	630000	34	95.28	75.64	0.058219	612800
12	1	0.6	0.00	1000500	34	95.28	75.64	0.058198	939800
13	1	0.6	0.45	26000	34	94.34	75.00	0.058430	14450
14	1	0.6	0.45	500350	32	97.17	76.28	0.057382	274400
15	1	0.6	0.45	1014900	36	96.23	76.92	0.057350	675800
16	1	0.6	0.90	26550	0	100.00	67.95	0.069861	25650
17	1	0.6	0.90	500900	0	100.00	67.95	0.069698	449200
18	1	0.6	0.90	1007550	0	100.00	67.95	0.069697	972450
19	1	0.9	0.00	26100	28	98.11	75.64	0.059558	7200
20	1	0.9	0.00	520050	32	97.17	76.28	0.057177	143650
21	1	0.9	0.00	1008250	32	97.17	76.28	0.057177	143600
22	1	0.9	0.45	26300	32	98.11	76.92	0.058304	12450

Table 2 (continued)

Test Number	Number of Nodes	Learning Rate	Momentum	Learning Events	Undamaged Kernels Correctly Classified %	Damaged Kernels Correctly Classified %	Total Kernels Correctly Classified %	Network Error[1]	Learning Events at Convergence[2]
23	1	0.9	0.45	690350	34	96.23	76.28	0.057436	627400
24	1	0.9	0.45	1257900	32	97.17	76.28	0.058046	138050
25	1	0.9	0.90	27200	0	100.00	67.95	0.060750	20400
26	1	0.9	0.90	520050	88	73.58	78.21	0.045563	68250
27	1	0.9	0.90	1002050	88	74.53	78.85	0.045563	68250
28	20	0.1	0.00	26000	36	91.51	73.72	0.056470	4600
29	20	0.1	0.00	520700	34	94.34	75.00	0.047229	283400
30	20	0.1	0.00	1144900	34	95.28	75.64	0.047198	1139000
31	20	0.1	0.45	26100	36	89.62	72.44	0.057998	4600
32	20	0.1	0.45	520000	34	94.34	75.00	0.045431	479600
33	20	0.1	0.45	1000400	34	94.34	75.00	0.045431	479600
34	20	0.1	0.90	30500	34	94.34	75.00	0.051757	24200
35	20	0.1	0.90	525000	34	94.34	75.00	0.051757	24200
36	20	0.1	0.90	1011550	34	93.40	74.36	0.051757	24200
37	20	0.6	0.00	26400	36	90.57	73.08	0.058597	11000
38	20	0.6	0.00	534200	36	93.40	75.00	0.040382	507200
39	20	0.6	0.00	1000000	34	95.28	75.64	0.039416	703400
40	20	0.6	0.45	26050	38	89.62	73.08	0.057801	2800
41	20	0.6	0.45	520050	78	90.57	86.54	0.042380	180200
42	20	0.6	0.45	1001550	76	90.57	85.90	0.042380	180200
43	20	0.6	0.90	26000	40	83.02	69.23	0.056841	8600
44	20	0.6	0.90	539100	82	76.42	78.21	0.044738	443600
45	20	0.6	0.90	1006300	82	76.42	78.21	0.044738	443600
46	20	0.9	00.0	26050	38	92.45	75.00	0.057622	24600

Table 2 (continued)

Test Number	Number of Nodes	Learning Rate	Momentum	Learning Events	Undamaged Kernels Correctly Classified %	Damaged Kernels Correctly Classified %	Total Kernels Correctly Classified %	Network Error[1]	Learning Events at Convergence[2]
47	20	0.9	0.00	501800	34	94.34	75.00	0.045875	467600
48	20	0.9	0.00	1000000	82	82.08	82.05	0.039484	864800
49	20	0.9	0.45	28250	36	90.57	73.08	0.055681	28000
50	20	0.9	0.45	522750	100	0.00	32.05	0.042707	157600
51	20	0.9	0.45	1002000	42	91.51	75.64	0.042707	157600
52	20	0.9	0.90	26800	40	81.13	67.95	0.056467	8600
53	20	0.9	0.90	532500	40	80.19	67.31	0.056467	8600
54	20	0.9	0.90	1007800	42	80.19	67.95	0.056467	8600
55	40	0.1	0.00	29000	36	88.68	71.79	0.056912	4600
56	40	0.1	0.00	522350	0	100.00	67.95	0.048114	519000
57	40	0.1	0.00	1000000	34	97.17	76.92	0.044808	954400
58	40	0.1	0.45	26250	34	94.34	75.00	0.058012	2800
59	40	0.1	0.45	521300	36	94.34	75.64	0.046987	516000
60	40	0.1	0.45	1003750	38	92.45	75.00	0.045344	954400
61	40	0.1	0.90	26000	36	83.96	68.59	0.055906	4800
62	40	0.1	0.90	520000	36	91.51	73.72	0.054926	519000
63	40	0.1	0.90	1000800	34	91.51	73.08	0.054604	584400
64	40	0.6	0.00	27900	36	89.62	72.44	0.061181	4200
65	40	0.6	0.00	527000	32	95.28	75.00	0.047013	271400
66	40	0.6	0.00	1276800	84	81.13	82.05	0.046528	644200
67	40	0.6	0.45	26050	36	83.02	67.95	0.060141	10600
68	40	0.6	0.45	521150	82	90.57	87.82	0.035970	269000
69	40	0.6	0.45	1036150	82	90.57	87.82	0.035970	269000
70	40	0.6	0.90	26050	24	97.17	73.72	0.053797	200

Table 2 (continued)

Test Number	Number of Nodes	Learning Rate	Momentum	Learning Events	Undamaged Kernels Correctly Classified %	Damaged Kernels Correctly Classified %	Total Kernels Correctly Classified %	Network Error[1]	Learning Events at Convergence[2]
71	40	0.6	0.90	574050	38	88.68	72.44	0.053505	554600
72	40	0.6	0.90	1003200	46	84.91	72.44	0.049368	989600
73	40	0.9	0.00	28000	34	92.45	73.72	0.062285	11800
74	40	0.9	0.00	501600	46	86.79	73.72	0.045250	498600
75	40	0.9	0.00	1000100	82	81.13	81.41	0.040325	632800
76	40	0.9	0.45	26600	36	91.51	73.72	0.058410	1600
77	40	0.9	0.45	521400	54	91.51	79.49	0.037964	137400
78	40	0.9	0.45	1109600	54	91.51	79.49	0.037964	137400
79	40	0.9	0.90	26050	0	100.00	67.95	0.053943	8600
80	40	0.9	0.90	536650	38	85.85	70.51	0.053943	8600
81	40	0.9	0.90	1000200	38	85.85	70.51	0.053943	8600

[1]Network error is the difference between the expected and actual outputs.
[2]Number of learning events undergone when the minimum network error was reached.

Table 3. Comparison of three levels of four variables of a neural network trained on 400 undamaged peanut kernels and 1200 damaged kernels and used to classify 44 good kernels and 112 damaged kernels.

Variable	Undamaged Average Correct (%)[1]	Damaged Average Correct (%)[1]	Total Average Correct (%)[1]	Minimum Network Error[2]
No. Nodes				
1	36.1b	92.1a	74.2a	0.05821a
20	46.9a	85.9a	73.4a	0.04947b
40	41.7ab	90.4a	74.8a	0.05012b
Learning Rate				
0.1	37.0a	91.1a	73.8a	0.05313a
0.6	43.2a	91.1a	75.7a	0.05292a
0.9	44.5a	86.3a	72.9a	0.05174a
Momentum				
0	41.8a	90.9a	75.2a	0.05154b
0.45	46.2a	88.4a	74.9a	0.05106b
0.9	36.8a	89.2a	72.4a	0.05520a
Learning Events				
26,000	32.8b	91.1a	72.4b	0.05838a
520,000	43.6a	87.7a	73.6ab	0.05012b
1,000,000	48.3a	89.7a	76.5a	0.04930b

[1]Means for each variable in columns followed by the same letter are not significantly different at P=0.05.

[2]Network error is the difference between the expected and actual outputs.

Table 4. Probability of a larger F (PR > F) for each variable and for all interactions of a neural network used to classify undamaged and damaged peanut kernels.

Variable	Undamaged Average Correct (PR > F)	Damaged Average Correct (PR > F)	Total Average Correct (PR > F)	Minimum Network Error[1] (PR > F)
No. Nodes (N)	0.33	0.62	0.72	0.01
Momentum (M)	0.38	0.61	0.11	0.03
Learning Rate (LR)	0.17	0.20	0.80	0.43
Learning Events (LE)	0.01	0.68	0.02	0.01
N*LR	0.01	0.05	0.06	0.02
N*M	0.31	0.43	0.40	0.19
N*LE	0.56	0.56	0.57	0.04
LR*M	0.50	0.62	0.08	0.30
LR*LE	0.05	0.12	0.29	0.72
M*LE	0.09	0.27	0.80	0.04
N*LR*M	0.01	0.11	0.09	0.01
LR*M*LE	0.29	0.61	0.15	0.11
N*LE*M	0.33	0.71	0.70	0.01
N*LR*LE	0.06	0.29	0.15	0.01

[1]Network error is the difference between the expected actual outputs.

Table 5. Linear and quadratic R^2 values for each variable tested in a neural network used to classify undamaged and damaged peanut kernels.

Variable	Undamaged R^2	Damaged R^2	Total[1] R^2	Minimum Network Error[1] R^2
Nodes				
Linear	0.011	0.003	0.002	0.175
Quadratic	0.042	0.046	0.008	0.258
Learning Rate				
Linear	0.022	0.021	0.001	0.005
Quadratic	0.023	0.033	0.033	0.006
Momentum				
Linear	0.009	0.003	0.031	0.037
Quadratic	0.032	0.007	0.037	0.056
Learning Events				
Linear	0.087	0.002	0.065	0.226
Quadratic	0.091	0.013	0.069	0.274

[1]Network error is the difference between the expected and actual outputs.

Table 6. Speed of convergence of a neural network used to classify damaged and undamaged peanut kernels. Values shown are the number of learning events undergone when the minimum network error was reached.

	Total Number of Learning Events During Training		
Variable	26,000[1]	520,000[1]	1,000,000[1]
No. Nodes			
1	15867a	352589a	490039a
20	13000ab	283556a	444556a
40	5467b	365956a	574978a
Momentum			
0	13272a	424161a	778956a
0.45	9033a	340467a	379406b
0.9	12028a	237472a	351211b
Learning Rate			
0.1	9339a	370978a	623156a
0.6	11300a	395822a	646450a
0.9	13694a	235300a	239967b

[1]Means for each variable in columns followed by the same letter are not significantly different at P=0.05.

Table 7. Damaged and undamaged peanut kernel classification accuracy of: 1) a neural network which utilized all wavelengths from 400 to 700 nm in 10 nm increments; 2) statistically selected line slopes and magnitudes of reflectance at 450, 520, and 670 nm; and 3) colorimeter L* a* b* values.

Method of Classification	Undamaged Correct (%)	Damaged Correct (%)	Total Correct (%)
1) Neural Network[1]	82.00	90.57	87.82
Statistics			
2) 3 wavelengths	98.00	63.21	74.36
3) Colorimeter (L*a*b*)	78.00	84.91	82.98

[1]Network parameters were nodes=40, learning rate=0.6, momentum=0.45, and learning events of 520,000 or 1,000,000.